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TABLE 1

HEALTH RISKS AND REVENUE LOSSES UNDER ALTERNATIVE RE-ENTRY INTERVALS

Re-entry interval (days)	Expected number of severe poisonings			Expected number of mild poisonings			Fraction of revenue lost
	California	Washington	Michigan	California	Washington	Michigan	
0-4	2.46050	1.63800	0.81650	42.6950	29.2650	15.0000	0
5	1.95600	1.33250	0.69100	34.5800	24.0600	12.7600	0.002397
6	1.57650	1.09650	0.59100	28.2250	19.9600	10.9500	0.004788
7	1.28550	0.91250	0.51050	23.2450	16.7150	9.4850	0.007174
8	1.06000	0.76750	0.44520	19.3150	14.1300	8.2900	0.009554
9	0.88350	0.65250	0.39155	16.2050	12.0600	7.3050	0.011928
10	0.74500	0.56000	0.34725	13.7200	10.3850	6.4900	0.014296
11	0.63400	0.48540	0.31045	11.7300	9.0250	5.8100	0.016659
12	0.54550	0.42450	0.27965	10.1200	7.9100	5.2350	0.019016
13	0.47340	0.37450	0.25370	8.8050	6.9900	4.7555	0.021368
14	0.41470	0.33315	0.23165	7.7300	6.2250	4.3460	0.023714
15	0.36960	0.29865	0.21290	6.8400	5.5900	3.9965	0.026054
16	0.32645	0.26970	0.19680	6.1050	5.0550	3.6965	0.028389
17	0.29305	0.24530	0.18295	5.4850	4.5995	3.4380	0.030718
18	0.26500	0.22450	0.17095	4.9515	4.2130	3.2135	0.033041
19	0.24125	0.20680	0.16000	4.5245	3.8825	3.0185	0.035359
20	0.22110	0.19155	0.15135	4.1495	3.5985	2.8480	0.037672
21	0.20385	0.17840	0.14335	3.8280	3.3530	2.6980	0.039978
22	0.18900	0.16700	0.13635	3.5515	3.1400	2.5660	0.042280
23	0.17620	0.15705	0.13010	3.3120	2.9540	2.4495	0.044575
24	0.16510	0.14835	0.12460	3.1040	2.7915	2.3465	0.046866
25	0.15540	0.14070	0.11970	2.9230	2.6485	2.2545	0.049150
26	0.14690	0.13400	0.11535	2.7640	2.5225	2.1725	0.051430
27	0.13945	0.12805	0.11145	2.6245	2.4110	2.0995	0.053704
28	0.12835	0.12275	0.10795	2.5010	2.3120	2.0340	0.055972

qt-tab.wp/dlw/12/23/88

Figure 1
Optimal Re-Entry Interval in California

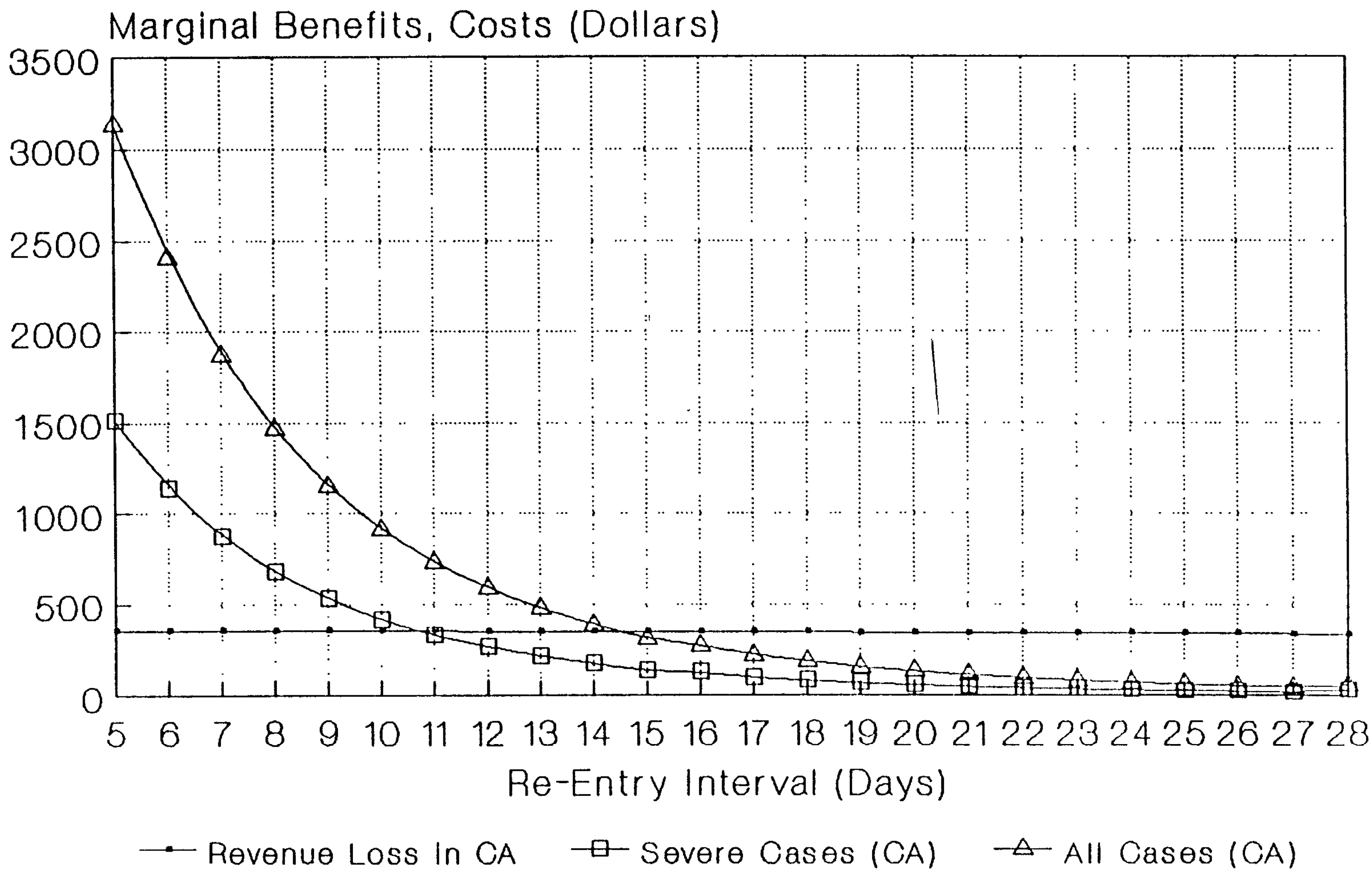


Figure 2
Optimal Re-Entry Interval in Washington

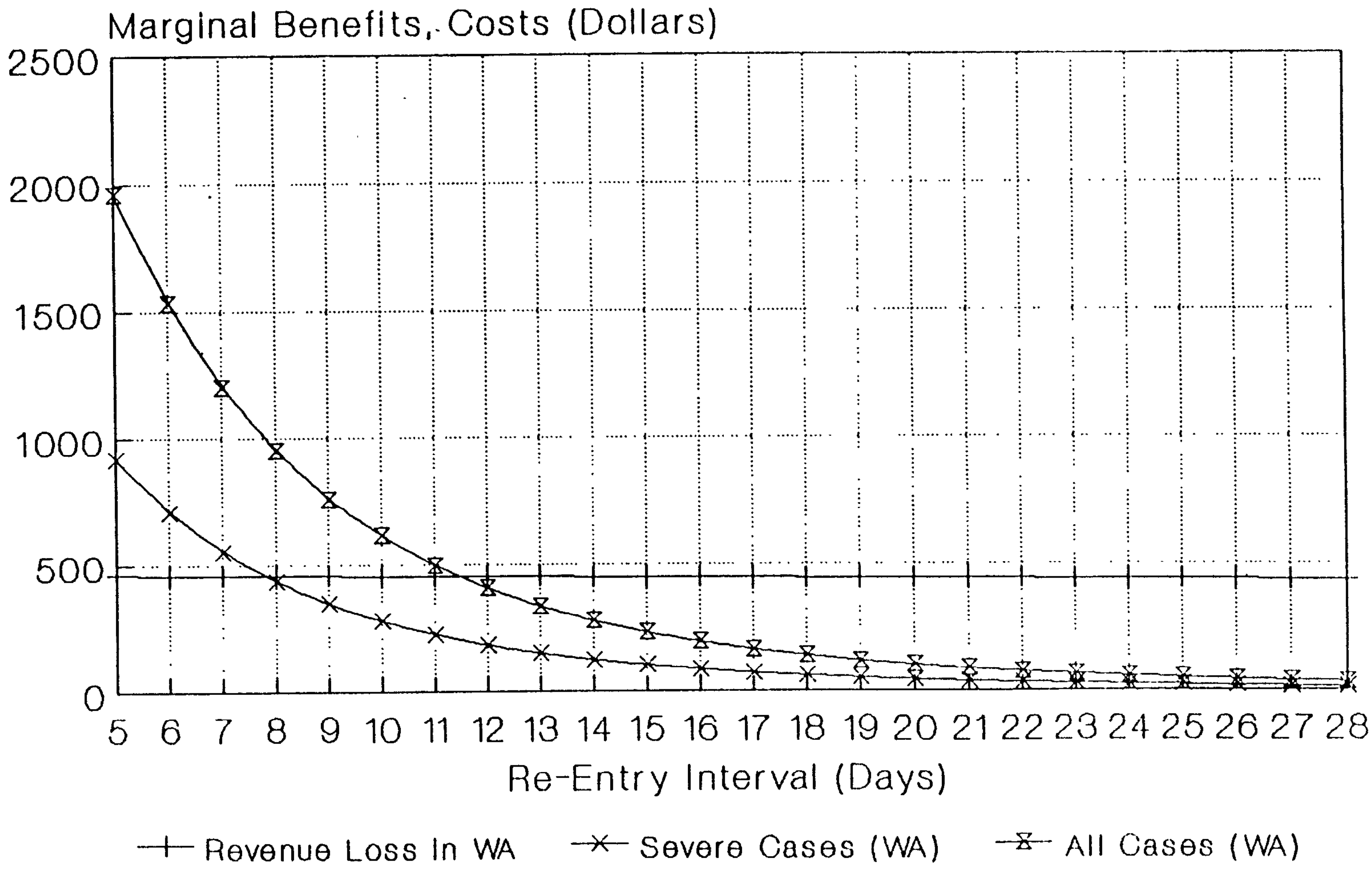
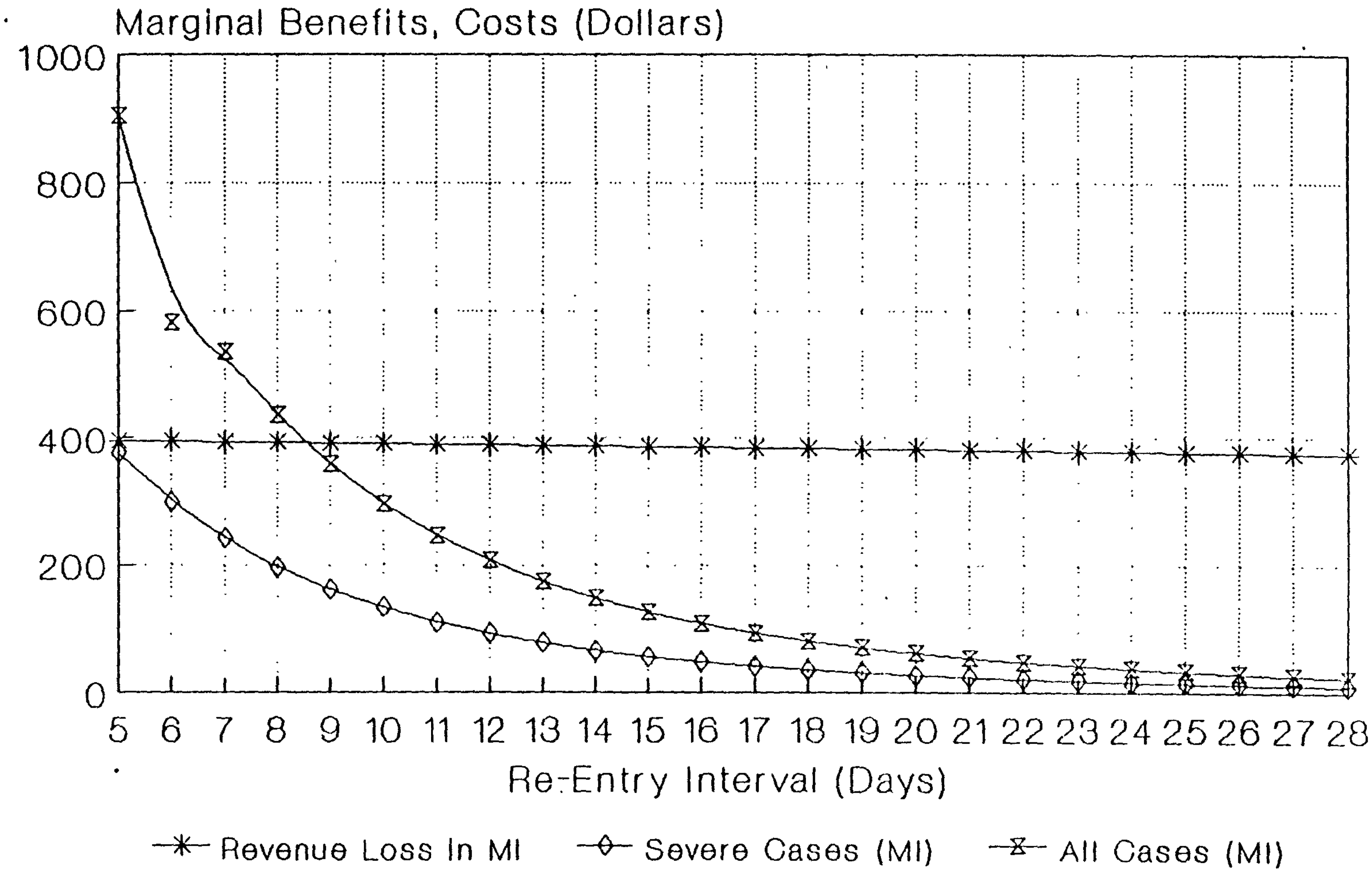


Figure 3
Optimal Re-Entry Interval In Michigan



VALUING REDUCED MORBIDITY: A HOUSEHOLD PRODUCTION APPROACH*

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ABSTRACT

This paper presents a unique application of the household production approach to valuing public goods and nonmarket commodities. Technical relationships are estimated between health attributes, private goods that affect health, and air quality using panel data drawn from a special survey. Statistical tests suggest that individuals equate marginal rates of technical substitution in household production with relevant price ratios. This result confirms that input choices are rational and is critical for estimating values of health attributes and air pollution. Value estimates obtained also bear on current questions facing environmental policymakers.

I. Introduction

Individuals frequently apply a household technology to combine public and private goods in the production of nonmarket commodities for final consumption. Hori (1975) demonstrates that in these situations, market prices of private goods together with production function parameters <u>may</u> encode enough information to value both public goods used as inputs and nonmarket final consumption commodities. Although this valuation methodology is objective and market based, it seldom has been applied for three reasons. First, underlying technical relations either are unknown or data needed to estimate them are unavailable. Second, even if relevant technical information is at hand, the consumer's budget surface in commodity space may not be differentiable when joint production and other complicating factors are present. As a consequence, the commodity bundle chosen is consistent with any number of marginal rates of substitution between commodities and values of public goods and nonmarket commodities remain unknown. Third, joint production and nonconstant returns to scale also pose serious difficulties when taking the closely related valuation approach of estimating the area behind demand curves for private goods inputs and final consumption commodities (Bockstael and McConnell 1983). The problems posed by joint production are, troublesome because Pollak and Wachter (1975) have argued that jointness is pervasive in home production, and Graham and Green (1985) found empirical evidence of substantial jointness in their estimation of a household technology.

This paper presents a unique application of the household production approach to valuing public goods and nonmarket commodities which allows for certain types of joint production and addresses key problems identified by previous authors. Technical relationships are estimated between health attributes, private goods, and air quality. Data used in the analysis are drawn from a special survey designed to implement the household production approach. Econometric estimates allow for censored dependent variables and cross-equation error correlations in panel data using tobit models with individual-specific variance components. Wilcox-Gök (1983, 1985) previously applied variance components estimation in a health context but did not examine censoring and cross-equation correlation. Key results of the present paper are: (1) attempts to value detailed attributes of nonmarket home produced commodities may be ill-advised; however, estimating a common value for a broadly defined category of attributes may be possible, and (2) statistical tests support the hypothesis that individuals equate marginal rates of technical substitution in household production with relevant price ratios. The latter result confirms that input choices are rational in the sense of Russell and Thaler (1985): choices are consistent with utility maximization subject to a correct understanding of the home technology. Also, value estimates obtained bear on current questions concerning air pollution control policy. The Clean Air Act of 1970 and its subsequent amendments focus primarily on health to justify regulation and require air quality standards to protect even the health of those most sensitive to pollution. The survey data are sufficiently rich to allow separate value estimates for persons with normal respiratory function and persons with chronic respiratory impairments.

The remainder of this paper is divided into four sections. Section II describes a simple household production model in a health context and reviews theoretical issues in obtaining value estimates. Section III discusses the survey instrument and the data collected. Section IV presents econometric estimates of production functions for health attributes, as well as values of better air quality and improved health for both the normal and respiratory impaired subsamples. Implications and conclusions are drawn out in Section V.

II. Preliminaries

The model specifies utility (U) as a function of market goods (Z) and health attributes, called symptoms, (S).

$$U = U(Z, S) \tag{1}$$

For simplicity, Z is treated as a single composite good, but S denotes a vector measuring intensity of n health symptoms such shortness of breath, throat irritation, sinus pain, headache, or cough. Intensity of the i^{th} symptom is reduced using a vector (V) of m additional private goods that do not yield direct utility, a vector of ambient air pollution concentrations (α), and an. endowment of health capital (Ω).

$$S^i = S^i(V, \alpha; \Omega) \qquad i = 1, \ldots, n \tag{2}$$

Elements of V represent goods an individual might purchase to reduce intensity of particular symptoms, and Ω represents genetic predisposition to experience symptoms or presence of chronic health conditions that cause symptoms. Notice that equation (2) allows for joint production in that some or all elements of V may (but do not necessarily) enter some or all symptom production functions.[1] The budget constraint is

$$I = P_Z Z + \Sigma_j P_j V_j \tag{3}$$

where P_Z denotes the price of Z, P_j denotes the price of V_j, and I denotes income.

Aspects of this general approach to modeling health decisions have been used in the health economics literature (e.g., Grossman 1972; Rosenzweig and Schultz 1982, 1983), where medical care is an example of V often considered. In these three papers, however, the stock of health rather than symptoms is treated as the home produced good, and Grossman treats decisionmaking intertemporally in order to analyze changes in the health stock over time. A multiperiod framework would permit a more complete description of air pollution's cumulative physiological damage, but the present model's focus on symptoms of short duration suggests that a one period model is appropriate. Moreover, long term panel data containing both economic and health information necessary to assess cumulative physiological damage are difficult to obtain.

Similar models also have been used in environmental economics to derive theoretically correct methods for estimating values of air quality and other environmental attributes (e.g., Berger et al. 1987, Courant and Porter 1981; Harford 1984; Harrington and Portney 1987). These models, however, only consider the case in which m = n = 1 and rule out the possibility of joint production. In this situation, the marginal value of or willingness to pay (WTP) for a reduction in air pollution can be derived by setting dU = 0 and using first order conditions to obtain

$$WTP_\alpha = - U_1 S^1_\alpha/\lambda = - P_1 S^1_\alpha/S^1_1 \qquad (4)$$

where U_1 denotes marginal disutility of the symptom, S^1_α denotes the marginal effect of air pollution on symptom intensity, S^1_1 denotes the marginal product of V_1 in reducing symptom intensity, and λ denotes marginal utility of income. As shown, marginal willingness to pay to reduce symptom intensity $(- U_1/\lambda)$ equals the marginal cost of doing so $(- P_1/S^1_1)$.

Extensions to situations where m and n take on arbitrary values have been considered in the theory of multi-ware production by Frisch (1965) as well as in a public finance context by Hori (1975). Actually, Hori treats four types of household production technology. His case (3) involving joint production appears to best characterize the application discussed in Section IV because a single V_j may simultaneously reduce more than one symptom. In this situation, a key result is that marginal values of home produced commodities cannot be re-expressed in terms of market prices and production function parameters unless the number of private goods is at least as great as the number of commodities ($m \geq n$). Intuitively, if $m < n$, the individual does not have a choice among some alternative combinations of symptom intensities because there are too few choice variables (V_j) and the budget surface on which each chosen value of S^i must lie is not differentiable.[2]

Another perspective on this result can be obtained from the first order conditions of the individual's utility maximization problem. After substituting. the symptom production functions into the utility function, the first order conditions include the budget constraint and

$$
\begin{aligned}
&U_z - \lambda P_z = 0 \\
&\Sigma_i U_i S_j^i - \lambda P_j = 0, \qquad j = 1, \ldots, m.
\end{aligned}
\tag{5}
$$

The marginal value of a reduction in air pollution is a weighted sum of the values of the individual symptom intensities (U_i/λ), where the weights are the marginal products of pollution (S_α^i): $WTP_\alpha = -\Sigma_i(U_i/\lambda)S_\alpha^i)$. Estimating values for reductions in symptoms or pollutants on the basis of observable behavior requires solving for the (U_i/λ) as functions of market prices of private goods and production function parameters. Rearranging the m first order conditions for the V_j gives

$$\begin{bmatrix} S_1^1 & \cdots & S_1^n \\ \cdot & & \\ \cdot & & \\ \cdot & & \\ S_m^1 & \cdots & S_m^n \end{bmatrix} \begin{bmatrix} U_1/\lambda \\ \cdot \\ \cdot \\ \cdot \\ U_n/\lambda \end{bmatrix} = \begin{bmatrix} P_1 \\ \cdot \\ \cdot \\ \cdot \\ P_m \end{bmatrix} \tag{6}$$

If $m < n$, the rank of the symptom technology matrix $S = \{S_j^i\}$ is at most m and the system of equations in (6) is underdetermined. Intensity of one symptom cannot be varied holding others constant, and the marginal value of an individual symptom cannot be determined. On the other hand, if $m = n$ and the symptom technology matrix is nonsingular, then the rank is n and unique solutions can be computed for the U_i/λ. If $m > n$ and the technology matrix has full rank, then the system is overdetermined, and values for the U_i/λ can be computed from a subset of the first order equations.

This theoretical overview yields several ideas useful in empirical application. First, if $m \geq n$ and the household technology matrix has rank n, then values of nonmarket commodities and public goods are calculated in a relatively straightforward manner because utility terms can be eliminated. Second, the possibility that m c n suggests that the household production approach may be incapable of estimating separate values for a comparatively large number of detailed commodities and that aggregation of commodities may be necessary to ensure $m > n$.[3] Third, even if $m \geq n$, the household production approach may fail if there is linear dependence among the rows of the technology matrix. Thus , statistical tests of the rank of the matrix should be performed to ensure differentiability of the budget surface. Fourth, if $m > n$, first order conditions impose constraints on values that can be taken by the S_j^1; rejection of these constraints would imply that the outcome of the choice process is inconsistent with utility-maximization subject to a known technology.

Fifth, if m > n, values of S_j^i and P_j need not yield positive values for $-U_i/\lambda$, the marginal willingness to pay to reduce intensity of the i^{th} symptom. Of course, in the simple case where m = n = 1, the only requirement is that $-P_1/S_1^1 > 0$. If m = n = 2, a case considered in the empirical work presented in Section IV, values of $-U_1/\lambda$ and $-U_2/\lambda$ both will be positive only if $(S_1^1/S_2^1) \gtrless (P_1/P_2) \gtrless (S_1^2/S_2^2)$. If V_1 and V_2 are not chosen such that their marginal rates of technical substitution bracket their price ratio, then it is possible to reduce intensity of one symptom without increasing intensity of the other and without spending more on symptom reduction.

Sixth, complications arise in expressing symptom and air pollution values in situations where some or all of the V_j are sources of direct utility, another form of joint production. This problem is important (and it is encountered in the empirical work presented in Section IV) because of the difficulty in identifying private goods that are purchased but do not enter the utility function. To illustrate, assume that m = 2, n = 1 and that V_2 -but not V_1 is a source of both direct positive utility and symptom relief. WTP_α still would equal $-(P_1S_\alpha^1/S_1^1)$ and therefore could be calculated without knowing values for marginal utility terms. If consumption of V_2, however, was used as a basis for this calculation, the simple formula $-(P_2S_\alpha^1/S_2^1)$ would overestimate WTP_α by an amount equal to $-(U_2S_\alpha^1/\lambda S_2^1)$ where U_2 denotes marginal utility of V_2 ($U_2 > 0$). When m and n take arbitrary values the situation is more complex, but in general nonmarket commodity and public good values can be determined only if the number of private goods which do not enter the utility function is at least as great as the number of final commodities. Even if this condition is not met, however, it is possible in some cases to determine whether the value of nonmarket commodities and public goods is over- or underestimated.[4] Each of these six issues is treated in the empirical work reported in Section IV. Although m = n = 2 and relevant marginal rates of technical substitution generally bracket input price ratios, statistical tests cannot reject the hypothesis that the technology matrix has rank one. After aggregating symptoms into one broad category, m > n (2 > 1), and first order conditions constrain the marginal rate of technical substitution to equal the price ratio. Failure to reject the constraint confirms that behavior is consistent with the model's predictions; nevertheless the likely possibility that both private good inputs are direct sources of utility suggests that the model's value estimates should be interpreted as lower bounds.

III. Data

Data used to implement the household production approach were obtained from a sample of 226 residents of two Los Angeles area communities. Each respondent previously had participated in a study of chronic obstructive respiratory disease (Detels et al. 1979, 1981). Key aspects of this sample are: (1) persons with physician diagnosed chronic respiratory ailments deliberately are overrepresented (76 respondents suffered from such diseases), (2) 50 additional respondents with self-reported chronic cough or chronic shortness of breath are included, (3) 151 respondents lived in Glendora, a community with high oxidant air Pollution and 75 respondents lived in Burbank, a community with oxidant pollution levels more like other urbanized areas in the U.S. but with high levels of carbon monoxide, (4) all respondents either were nonsmokers or former smokers who had not smoked in at least two years, and (5) all respondents were household heads with full-time jobs (defined as at least 1,600 hours of work annually).

professionally trained interviewers contacted respondents several times over a 17 month period beginning in July 1985. The first contact involved administration of an extensive baseline questionnaire in the respondent’s home. Subsequent interviews were conducted by telephone.[5] Including the baseline interview, the number of contacts with each respondent varied from three to six with an average number of contacts per respondent of just over five. Of the 1147 total contacts ($\cong$ 226 x 5), 644 were with respiratory impaired subjects (i.e., those either with physician-diagnosed or self-reported chronic respiratory ailments) and 503 were with respondents having normal respiratory function.

Initial baseline Interviews measured four groups of variables: (1) long term health status, (2) recently experienced health symptoms, (3) use of private goods and activities that might reduce symptom intensity, and (4) socioeconomic/demographic and work environment characteristics. Telephone follow-up interviews inquired further about health symptoms and use of particular private goods. Long term health status was measured in two ways. First, respondents indicated whether a physician ever had diagnosed asthma (ASTHMA), chronic bronchitis (BRONCH), or other chronic respiratory disease such as emphysema, tuberculosis, or lung cancer. Second, they stated whether they experience chronic shortness of breath or wheezing (SHRTWHZ) and/or regularly cough up phlegm, sputum, or mucous (FLEMCO). Respondents also indicated whether a physician ever had diagnosed hay fever (HAYFEV); however, this condition was not treated as indicative of a chronic respiratory impairment.

Both background and follow-up instruments also asked which, if any, of 26 health symptoms were experienced in the two days prior to the interview. Symptoms initially were aggregated into two categories defined as: (1) chest and throat symptoms and (2) all other symptoms.[6] Aggregation to two categories reduces the number of household produced final goods (n) considered; however, assigning particular symptoms to these categories admittedly is somewhat arbitrary. Yet, the classification scheme selected permits focus on a group of symptoms in which there is current policy interest. Chest and throat symptoms identified have been linked to ambient ozone exposure (see Gerking et al. 1984, for a survey of the evidence) and federal standards for this air pollutant currently are under review. Moreover, multivariate tobit turns out to be a natural estimation method and aggregating symptoms into two categories permits a reduction in computation burden. Dickie et al. (1987(a)) report that respondents with chronic respiratory impairments experienced _each_ of the 26 individual symptoms more often than respondents with normal respiratory function. This outcome is reflected in Table 1 which tabulates frequency distributions of the total number of chest and throat and other symptoms reported by respondents in the two subsamples.[7]

In the empirical work reported in Section IV, data on the number of symptoms reported are assumed to be built up from unobserved latent variables measuring symptom intensity. As intensity of a particular symptom such as cough rises above a threshold, the individual reports having experienced it; otherwise he does not. Thus, the frequency distribution tabulated in Table 1 merely reflects the number of symptoms that crossed the intensity threshold in the two days prior to the interview.

Private goods used to estimate symptom production functions include durable goods which may relieve symptoms by reducing exposure to air pollution. When asked during the baseline interview whether they changed their activities at all when the air was smoggy, half the respondents in the impaired group and 42 percent of the respondents in the normal group reported that they tried to stay indoors and/or run their air conditioners more in an attempt to avoid the pollution. The effectiveness of such a strategy depends on the quality of the indoor air, which in turn depends partly on whether the respondent has and uses the following private goods: (1) central air conditioning in the home (ACCEN), (2) an air purifying system in the home, and (3) a fuel other than natural gas for cooking (NOTGASCK).[8] Similarly, a respondent who has and used air conditioning in the automobile (ACCAR) might reduce exposure to pollution, particularly when driving or idling in traffic. Each of these private goods may provide direct utility in addition to reducing exposure to pollution. Air conditioners, for example, may provide not only relief from symptoms but also cooling services that yield direct satisfaction. This problem is discussed further in Section V.

Socioeconomic/demographic variables measured whether the respondent lived in Burbank or Glendora (BURB) as well as years of age (AGE), gender, race (white or nonwhite), marital status, and household income. Also, respondents were asked whether they were exposed to toxic fumes or dust while at work (EXPWORK).

Finally, each contact with a respondent was matched to measures of ambient air pollution concentrations, humidity, and temperature for that day. Air monitoring stations used are those nearest to residences of respondents in each of the two communities. Measures were obtained of the six criteria pollutants for which national ambient air quality standards have been established: carbon monoxide (CO), nitrogen dioxide (NO_2), ozone (O_3), sulfur dioxide (SO_2), lead and total suspended particulate. Readings for lead and particulate, however, only were available for about ten percent of the days during the study period, forcing exclusion of those pollutants from empirical work. Each of the remaining four pollutants were measured as maximum daily one-hour ambient concentrations. Maxima are used because epidemiological and medical evidence suggests that acute symptoms may be more closely related to peak than to average pollution concentrations. The air pollution variables entered then, are averages of one hour maxima on the two days prior to the interview so as to conform with the measurement of symptoms.[9] Temperature and relative humidity data similarly were averaged across two day periods.

IV. Estimates of Household Symptom Technology

This section reports estimated production functions, hypothesis tests, and estimated values of public goods and nonmarket commodities. A bivariate tobit model with variance components was developed to account for: (1) probable correlation of disturbances across production functions, (2) censoring of reported symptoms at zero, and (3) repeated observations of the same individuals at different times.[10] Both tobit and variance components models frequently are applied; however, as discussed by Maddala (1987), there have been few applications of tobit with variance components to panel data.

Empirical estimates of household production functions for health also have been obtained by Rosenzweig and Schultz (1983)[11] and variance components models have been applied to health production by Wilcox-Gök (1983, 1985)[12]; however, neither of these investigators focus on valuing nonmarket commodities and public goods. Rosenzweig and Schultz consider birthweight rather than symptoms and Wilcox-Gök examines days missed from usual activities due to illness or injury and visits to certain health care facilities. Although the dependent variables used by Wilcox-Gök would appear to be correlated and censored at zero, the estimation procedures employed by Wilcox-Gök did not correct for either problem. In contrast, the bivariate tobit model presented below allows for both censoring and cross-equation error correlation.

The symptom production functions are specified as

$$S^i_{ht} = \begin{cases} X'_{ht}\beta_i + \varepsilon_{iht} & \text{if } X'_{ht}\beta_i + \varepsilon_{iht} > 0 \\ 0 & \text{otherwise} \end{cases} \qquad (7)$$

$$i = 1, 2.$$

In equation (7), i denotes type of symptom (chest and throat = 1, other = 2), h denotes respondent, and t denotes time; S^i_{ht} represents the number of symptoms reported and X_{ht} is a vector including explanatory variables such as measures of health capital, private goods, and air pollutants.

Random disturbances consist of the sum of a transitory component and a permanent component common to both production functions

$$\varepsilon_{iht} = \mu_h + \nu_{iht} \qquad i = 1, 2 \qquad (8)$$

The transitory error components, ν_{iht}, capture unmeasured influences that vary over individuals, symptoms, or time. The permanent error component, μ_h, varies only over individuals, capturing unmeasured individual specific influences that persist over time. The assumption that the same permanent component enters both production functions results in computational savings and is at least plausible, since the same individual produces both categories of symptoms.

Permanent components are assumed normally and independently distributed with mean zero and variance σ_μ^2. Transitory components are assumed normally and independently distributed, conditional on the permanent component, with mean zero and variance σ_i^2, i = 1, 2. Despite the common permanent component, the correlation coefficient between the two symptom classes in the same time period, $\sigma_\mu^2/(\sigma_\mu^2 + \sigma_1^2)^{\frac{1}{2}}(\sigma_\mu^2 + \sigma_2^2)^{\frac{1}{2}}$, is distinct from the correlation coefficient between the same symptom class at different times, $\sigma_\mu^2/(\sigma_\mu^2 + \sigma_i^2)$, i = 1, 2.

Let F_{iht} and f_{iht} represent, respectively, the normal distribution and density functions evaluated at $(S_{ht}^i - X_{ht}'\beta_i - \mu_h)/\sigma_i$, conditional on μ_h. The log-likelihood function is

$$L = \Sigma_h \ln \int \Pi_i [\prod_{S_{ht}^i=0} F_{iht} \cdot \prod_{S_{ht}^i>0} f_{iht}] g(\mu) d\mu \tag{9}$$

where $g(\cdot)$ is the normal density.[13]

An alternative to the variance components or random effects model is the fixed effects model in which the μ_h are treated as fixed constants rather than as random variables. Two arguments can be made in favor of the random effects specification of the symptom production model.[14]

First, treating the μ_h as constants subsumes the effects of all individual specific, time invariant variables into the fixed effects. Since the private goods measured in the data are fixed during the sampling period, using the fixed effects model would make it impossible to identify the production function parameters (S_j^1) necessary to estimate values for reductions in symptoms and air pollutants. Similarly, estimating the separate effects for the various chronic health impairment variables is of some interest, but these effects could not be distinguished from the μ_h in the fixed effects specification.

The second argument in favor of random effects rests on the inconsistency of the fixed effects tobit estimator. The individual effects μ_h cannot be estimated consistently for a small number of time periods even as the number of individuals increases without bound. Intuitively, each individual brings to the sample a distinct μ_h, with the result that increasing the number of individuals fails to increase the information available to estimate the μ_h. In many nonlinear models, including tobit, fixed effects estimators for the remaining parameters cannot be derived independently of the μ_h, so that the entire set of parameters is estimated inconsistently. By contrast, the random effects model attempts to estimate only the mean and variance of the μ_h rather than the individual effects themselves and thus can estimate the slope coefficients of the model consistently.

While these arguments present a compelling case for the random effects model, biased estimation can result because the model ignores the correlation that may exist between the explanatory variables and the permanent error component (see, e.g., Mundlak 1978). For example, if an individual knows his own μ_h, utility maximization would imply that his choice of private goods depends on μ_h. A solution to this problem proposed for probit models by Chamberlain (1980) is to specify μ_h as a linear function of the individual's explanatory variables plus an orthogonal residual: $\mu_h = X_h'\Pi + \eta_h$, where X_h' includes the individual's entire time series of observations on explanatory variables. This auxiliary regression then could be substituted for μ_h in the specification of the symptom production functions, and the likelihood derived by integrating over the density of n rather than the density of μ. But owing to the lack of temporal variation in all explanatory variables except the measures of pollution and weather, the substitution would produce collinearity in the matrix of explanatory variables as each time-invariant variable in the auxiliary regression above would be perfectly collinear with its counterpart already included in the model specification. As a consequence, Chamberlain's approach was not pursued.

An alternative approach to correct for correlation between covariates and errors is analogous to the two stage least squares procedure employed by Rosenzweig and Schultz in their previously cited birthweight study. In the first stage, reduced form probit demand equations for each of four private goods (ACHOME, ACCAR, APHOME, NOTGASCK) are estimated.[15] In the second stage, predicted probabilities from the reduced form probits were to be used as instruments for private goods in the tobit symptom production function models, but explanatory power of the reduced form probit equations was very poor. In half of the equations for each subsample the null hypothesis that all slope coefficients jointly are zero could not be rejected at the 5 percent level and in all equations key variables such as household income had insignificant and often wrongly signed coefficients. Another problem is the absence of private good price data specific to each respondent. The original survey materials requested these data but after pretesting, this series of questions was dropped because many respondents often made purchases jointly with 3 house or car and were unable to provide even an approximate answer. As a consequence, two-stage estimation was not pursued further with the likely outcome that estimates of willingness to pay for nonmarket commodities and public goods may have a downward bias.

Tables 2 and 3 present illustrative symptom production function estimates for impaired and normal subsamples. Equations presented are representative of a somewhat broader range of alternative specifications available from the authors on request. The overall explanatory power of the model was evaluated by testing the null hypothesis that all estimated coefficients (excepting the constant terms) jointly are zero. A Likelihood ratio tests rejects this hypothesis for both subsamples at significance levels less than one percent. Also, estimates of the individual specific error components, denoted σ_μ, have large asymptotic t-statistics which confirms persistence of unobserved personal characteristics that affect symptoms.

Table 2 shows that chronic health ailments and hay fever are positively related to symptom occurrence among members of the impaired group. Coefficients of ASTHMA, BRONCH, SHRTWHZ, and HAYFEV are positive in equations for both chest and throat and other symptoms and have associated asymptotic t-statistics that range from 2.1 to 7.6. The coefficient of FLEMCO is positive and significantly different from zero at conventional levels in the chest and throat equation, but its asymptotic t-statistic is less than unity in the equation for other symptoms. The coefficient of AGE was not significantly different from zero in either equation and the EXPWORK variable was excluded because of convergence problems with the bivariate tobit algorithm.[16] Variables measuring gender, race, and marital status never were included in the analysis because 92 percent of the impaired respondents were male, 100 percent were white, and 90 percent were married. Residents of Burbank experience chest and throat symptoms with less frequency than do residents of Glendora. Of course, many possible factors could explain this outcome; however, Burbank has had a less severe long term ambient ozone pollution problem than Glendora. For example, in 1986 average one day hourly maximum ozone readings in Burbank and Glendora were 8.7 pphm and 10.2 pphm, respectively, and a similar difference in ozone readings has persisted at least since 1983.

With respect to private and public inputs to the symptom production functions, the coefficient of ACCAR is negative and significantly different from zero at the 10 percent level using a one tail test in the other symptoms equation, while the coefficient of ACCEN is negative and significantly different from zero at the 5 percent level using a one tail test in both equations. Results from estimated equations not presented reveal that NOTGASCK and use of air purification at home never are significant determinants of symptoms in the impaired subsample. Also, 03, CO, and N02 exert insignificant influences on occurrence of both types of symptoms. When four air pollution variables were entered, collinearity between them appeared to prevent the maximum likelihood algorithm from converging. Consequently, S02 was arbitrarily excluded from the specification presented and the three air pollution measures included as covariates should be interpreted as broader indices of ambient pollutant concentrations. Variables measuring temperature and humidity were excluded from the Table 2 specification; but in equations not reported their coefficients never were significantly different from zero.

Table 3 presents corresponding symptom production estimates for the subsample with normal respiratory function. HAYFEV is the only health status variable entered because ASTHMA, BRONCH, SHRTWZ, and FLEMCO were used to define the impaired subsample. Coefficients of HAYFEV are positive in equations for both chest and throat and other symptoms and have t-statistics of 1.61 and 1.87, respectively. Coefficients of BURB are negative; but in contrast to impaired subsample results, they are not significantly different from zero at conventional levels. AGE and EXPWORK enter positively and their coefficients differ significantly from zero at 2½ percent in the other symptoms equation. Among private goods entering the production functions, coefficients of APHOME and ACHOME never were significantly different from zero at conventional levels, and these variables are excluded from the specification in Table 3. Use of air conditioning in an automobile reduced chest and throat symptom occurrences and cooking with a fuel other than natural gas (marginally) reduces other symptoms. Variables measuring gender, race, and marital status again were not considered as the normal subsample was 94 percent male, 99 percent white, and 88 percent married. In the normal subsample, collinearity and algorithm convergence problems again limited the number of air pollution variables that could be entered in the same equation. As shown in Table 3, O_3, CO and NO_2 coefficients had associated t-statistics of 1.16 or smaller. Temperature and humidity variables are excluded from the specification shown in Table 3. In alternative specifications not reported, coefficients of these variables never were significantly different from zero in alternative equations not reported.

Three pieces of information are required to use the estimates in Tables 2 and 3 in the calculation of values for reductions in symptoms and air pollutants: (1) marginal effects of air pollutants on symptoms, (2) marginal effects of private goods on symptoms, and (3) prices of private goods. Marginal products were defined as the effect of a small change in a good on the expected number of symptoms. Computational formulae were developed extending results for the tobit model (see McDonald and Moffit 1980) to the present context which allows for variance components error structure. However, because private goods are measured as dummy variables and, therefore, cannot be continuously varied, incremental, rather than marginal, products are used.

The final elements needed to compute value estimates are the prices of private goods. Dealers of these goods in the Burbank and Glendora areas were contacted for estimates of initial investment required to purchase the goods, average length of life, scrap value (if any), and fuel expense. After deducting the present scrap value from the initial investment, the net initial investment was amortized over the expected length of years of life. Adding annual fuel expense yields an estimate (or range of estimates) of annual user cost of the private good. The annual costs then were converted to two-day costs to match the survey data.[17] The dependent variables used in the estimated equations do not distinguish between one- and two-day occurrences of symptoms, but approximately one-half of the occurrences were reported as two day occurrences. As a consequence, the value estimates obtained were divided by 1.5 to convert to daily values.

Two tests were performed prior to estimating values of symptom and air pollution reduction. First, calculations were made for both normal and impaired subsamples to ensure that relevant ratios of incremental products of private goods in reducing symptoms bracketed the corresponding price ratio. Recall from the discussion in Section II that this condition guarantees that value estimates for reducing both types of symptoms are positive. A problem in making this calculation is that estimates of incremental rates of technical substitution vary across individuals (incremental products are functions of individual characteristics), but no respondent specific price information is available. As just indicated, dealers in Glendora provided the basis for a plausible range of prices to be constructed for each good. If midpoints of relevant price ranges are used together with incremental rates of technical substitution taken from Tables 2 and 3, the bracketing condition is met for all 100 respondents in the normal subsample and 117 of 126 respondents in the impaired subsample. Of course, alternative price ratios selected from this range meet the bracketing condition for different numbers of respondents.

Second, possible singularity of the symptom technology matrix was analyzed using a Wald test (see Judge et al. 1985, p. 215 for details).[18] In the context of estimates in Tables 2 and 3, the distribution of the test statistic (λ) is difficult to evaluate because relevant derivatives are functions of covariate values and specific to individual respondents. However, if derivatives are evaluated in terms of the underlying latent variable model, they can be expressed in terms of parameters only and A is distributed as χ^2 with 1 degree of freedom. Adopting this simpler approach, p-values for the Wald test statistic are large: p = .742 for the impaired subsample equations and p = .610 for the normal subsample equations.[19] As a consequence, the null hypothesis of singularity of the symptom technology matrix is not rejected at conventional levels. This result suggests that in both subsamples, there does not appear to be an independent technology for reducing the two types of symptoms, budget constraints are nondifferentiable, and separate value estimates for chest and throat and other symptoms should not be calculated.

A common value for reducing chest and throat and other symptoms still can be obtained by aggregating the two categories and re-estimating production functions in a univariate tobit framework. Table 4 shows results based on using the same covariates as those reported in Tables 2 and 3 and retaining the variance components error structure. The Table 4 equations also make use of a constraint requiring that if m > n = 1, the marginal rate of technical substitution must equal the input price ratio to insure that values of marginal willingness to pay to avoid a symptom must be identical no matter which private good is used as the basis for the calculation. In the case where m = 2 and n = 1, as discussed in Section II this single value is $-U_1/\lambda = -(P_1/S_1^1) = -(P_2/S_2^1)$. In the impaired subsample, the restriction can be tested under the null hypothesis, $H_0 : \beta_{ACCAR} = (P_{ACCAR}/P_{ACHOME})\beta_{ACHOME}$, where the β_i are coefficients of ACCAR and ACHOME in the latent model and the P_i are midpoints from the estimated range of two day prices for the private goods. In corresponding notation, the null hypothesis to test in the normal subsample is, $H_0 : \beta_{ACCAR} = (P_{ACCAR}/P_{NOTGASCK})\beta_{NOTGASCK}$. Both hypotheses are tested against the alternative that coefficients of private goods are unconstrained parameters, using a likelihood ratio test.

P-values for the parameter restrictions are comparatively large; P = .623 in the impaired subsample and P = .562 in the normal subsample. Thus, the above null hypotheses are not rejected at conventional significance levels. This result supports a critical implication of the previously presented household production model, namely that individuals equate marginal rates of technical substitution in production with relevant price ratios. Moreover, coefficients of private good variables defined under the null hypotheses for the two subsamples have t-statistics exceeding two in absolute value. Performance of remaining variables is roughly comparable to the bivariate tobit estimates. A notable exception, however, is that in the normal subsample univariate tobit estimates, coefficients of 03 and NO2 are positive with t-statistics exceeding 1.6. This outcome suggests that persons with normal respiratory function tend to experience more symptoms when air pollution levels are high, whereas those with impaired respiratory function experience symptoms with such regularity that there is no clear relationship to fluctuations in air quality. Intensity of particular symptoms may be greater in both subsamples when pollution levels are high, but this aspect is not directly measured.

Table 5 presents estimates of marginal willingness to pay to avoid symptoms and to reduce two air pollutants. Unconditional values of relieving symptoms and reducing air pollution are calculated for each respondent from observed univariate tobit models. Table 5 reports the mean, median, and range of respondents' marginal willingness to pay to eliminate one health symptom for one day as well as mean marginal willingness to pay to reduce air pollutants by one unit for one day for the normal subsample. Symptom reduction values range from $0.81 to $1.90 in the impaired subsample and from $0.49 to $1.22 in the normal subsample with means of $1.12 and $0.73 in the two subsamples, respectively.[20] Also, values of willingness to pay to reduce one hour daily maximum levels of 03 and NO2 by one part per ten million are $0.31 and $0.91 in the normal subsample. Corresponding calculations are not reported for the impaired subsample because, as shown in Table 4, coefficients of air pollution variables are not significant at conventional levels.

V. **Conclusion**

Willingness to pay values of symptom reduction and air quality improvement just presented should be viewed as illustrative approximations for two reasons. First, private goods used in computing the estimates are likely to be direct sources of utility. Second, symptom experience and private good purchase decisions are likely to be jointly determined. Nevertheless, these estimates still are of interest because aspects of joint production are taken into account. A key finding is that independent technologies for home producing symptoms are difficult to identify, thus greatly limiting the number of individual symptoms for which values can be computed. In fact, the 26 symptoms analyzed here had to be aggregated into a single group before willingness to pay values could be computed.

This outcome appears to have implications for estimating willingness to pay for nonmarket commodities in other contexts. An obvious example concerns previous estimates of willingness to pay to avoid health symptoms. Berger et al. (1987) report one day willingness to pay values for eliminating each of seven minor health symptoms, such as stuffed up sinuses, cough, headache and heavy drowsiness that range from $27 per day to $142 per day. Green et al. (1978) present estimates of willingness to pay to avoid similarly defined symptoms ranging from $26 per day to $79 per day. In both studies, however, willingness to pay estimates were obtained symptom by symptom in a contingent valuation framework that ignores whether independent technologies are available to produce each. Thus, respondents simply may have lumped total willingness to pay for broader health concerns onto particular symptoms. Some respondents may also have inadvertently stated their willingness to pay to avoid symptoms for periods longer than one day.

Another example relates to emerging research aimed at splitting willingness to pay to reduce air pollution into health, visibility, and possibly other components. From a policy standpoint, this line of inquiry is important because the Clean Air Act and its subsequent amendments focus primarily on health and give less weight to other reasons why people may want lower air pollution levels. Analyzing location choice within metropolitan areas, for example, may not provide enough information to decompose total willingness to pay into desired components. Instead, survey procedures must be designed in which respondents are either reminded of independent technologies that can be used to home produce air pollution related goods or else confronted with believable hypothetical situations that allow one good to vary while others are held constant.

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FOOTNOTES

[1]Another, possibly troublesome, aspect of joint production occurs if some or all elements of V are arguments in the utility function. This complication is discussed momentarily.

[2]Hori identifies three sources of nondifferentiability of the budget surface under joint production. The first occurs if the number of private goods is less than the number of commodities. The second arises because of nonnegativity restrictions on the private goods. This is not treated directly in the present paper, but if each private good is purchased in positive quantities, the chosen commodity bundle will not lie at the second type of kink. Hori's third cause of nondifferentiability implies linear dependence among the rows of the technology matrix, a possibility considered below.

[3]Notice that this point on aggregation may apply to other valuation methods as well. Using contingent valuation surveys, for example, Green et al. (1978) and Berger et al. (1987) obtained value estimates of several specific symptoms; however, issues relating to existence of independent symptom technologies never was faced. Future contingent valuation surveys may do well to consider this point prior to eliciting estimates of willingness to pay.

[4]For example, suppose m = n = 2 and both private goods are direct sources of utililty. If equation (6) is used to solve for the U_i/λ, then: (1) if the two marginal rates of technical substitution (MRTS) do not bracket the price ratio, then the value of the commodity whose

MRTS is closer in magnitude to the price ratio will be overestimated, while the value of the other commodity will be underestimated; (2) if the two MRTS values do bracket the price ratio, then the value of either one or both of the commodities will be overestimated; and (3) in no case will the value of both commodities be underestimated.

[5]Both questionnaires are presented and extensively discussed in Volume II of Dickie et al. (1987(b)).

[6]Chest and throat symptoms include (1) cough, (2) throat irritation, (3) husky voice, (4) phlegm, sputum or mucous, (5) chest tightness, (6) could not take a deep breath, (7) pain on deep respiration, (8) out of breath easily, (9) breathing sounds wheezing or whistling. Other symptoms are (1) eye irritation, (2) could not see as well as usual, (3) eyes sensitive to bright light, (4) ringing in ears (5) pain in ears, (6) sinus pain, (7) nosebleed, (8) dry and painful nose, (9) runny nose, (10) fast heartbeat at rest, (11) tired easily, (12) faintness or dizziness, (13) felt spaced out or disoriented, (14) headache, (15) chills or fever, (16) nausea, and (17) swollen glands.

[7]An alternative to counting the number of different symptoms experienced in the two days prior to the interview would be to consider the number of symptom/days experienced. Both approaches were used to construct empirical estimates; however, to save space, only those based on counts of different symptoms are reported. Both approaches yield virtually identical value estimates for symptom and air pollution reduction.

[8]Cooking with a fuel other than natural gas reduces exposure because gas stoves emit nitrogen dioxide.

[9]The equations also were estimated after defining the pollution variables as the largest of the one hour maxima on the two days; similar results were obtained.

[10]Although there is a linear relationship between the latent dependent variables and the private goods in the tobit model, the relationship between the observed dependent variables and the private goods has the usual properties of a production function. The expected number of symptoms is decreasing and convex (nonstrictly) in the private goods.

[11]Rosenzweig and Schultz also initially specify their production functions in translog form and then test whether restrictions to CES and Cobb-Douglas forms are justified. This type of analysis is not pursued here as most of the covariates used are 0-1 dummy variables. Squaring these variables does not alter their values. Interaction variables of course, still could be computed.

[12]Wilcox-Gök used variance components to control for family-specific effects in pooled sibling data rather than for individual-specific effects in pooled cross section-time series data.

[13]The tobit coefficients and variances of the model are estimated by maximizing the likelihood function using the method of Berndt, Hall, Hall, and Hausman (1974). The score vectors are specified analytically and the information matrix is approximated numerically using the summed outer products of the score vectors. Starting values for the coefficients and the standard deviations of the transitory error components were obtained from two independent tobit regressions with no permanent error component. In preliminary runs a starting value of unity was used for the standard deviation of the permanent error component, but the starting value was

adjusted to 1.5 after the initial estimate was consistently greater than one.

[14]The following discussion draws heavily on Hsiao (1986) and Maddala (1987).

[15]Covariates in the reduced form regressions are: ASTHMA, BRONCH, FLEMCO, SHRTWZ, HAYFEV, BURB, AGE, EXPWORK, years of education, number of dependents, household income, and an occupation dummy variable measuring whether respondent is a blue collar worker.

[16]In the impaired subsample, inclusion of EXPWORK frequently caused the bivariate tobit algorithm to fail to converge. This problem arose in the specification presented in Table 2; consequently the EXPWORK variable was excluded.

[17]The estimated two-day prices are: \$2.34 for ACCEN, \$1.00 for ACCAR, \$0.80 for NOTGASCK. The discount rate was assumed to be 5 percent. For further details of the procedure used to estimate prices, see Dickie et al. (1987(a)).

[18]The Wald test was chosen because its test statistic can be computed using only the unconstrained estimates. Since the likelihood and constraint functions both are nonlinear, re-estimating the model with the constraint imposed would be considerably more difficult than computing the Wald test statistic. Gregory and Veall (1985) identified a problem with Wald tests of nonlinear restrictions: changing the restriction into a form that is algebraically equivalent under the null hypothesis will change the p-value of the test. To check for this problem, the constraint was tested in two forms. The first, reported in the text, is $H_0 : S_1^1 S_2^2 - S_2^1 S_1^2 = 0$. The second is $S_1^1/S_2^1 - S_1^2/S_2^2 = 0$. In all cases both tests yielded nearly identical p-values.

[19]In other estimates of symptom production functions not reported here, corresponding p-values also are large, almost always exceeding .25 and sometimes the .80-.90 range.

[20]For comparison purposes, mean values also were estimated at subsample means of all explanatory variables. Results differ little with means computed over respondents. Evaluated at subsample means, willingness to pay to eliminate one symptom for one day is $1.05 in the impaired subsample and $0.70 in the normal subsample.

TABLE 1.--FREQUENCY DISTRIBUTIONS OF SYMPTOMS BY SUBSAMPLE

	Number of Chest and Throat Symptoms Experienced in Past Two Days		Number of Other Symptoms Experienced In Past Two Days	
	Impaired	Normal	Impaired	Normal
0	351	408	257	338
1	84	41	123	79
2	64	18	85	42
3	48	15	73	18
4	37	9	45	12
5	26	4	28	5
6	16	6	14	6
7	8	2	9	2
8	8	0	4	1
9	2	0	2	0
10	0	0	1	0
11	0	0	1	0
12	0	0	2	1
13	0	0	0	0
14	0	0	0	0
15	0	0	0	0
16	0	0	0	0
17	0	0	0	0
Sample Mean	1.348	0.453	1.668	0.692

TABLE 2.--BIVARIATE TOBIT SYMPTOM PRODUCTION FUNCTION ESTIMATES: IMPAIRED SUBSAMPLE[a]

	Chest and Throat Symptoms	Other Symptoms
CONSTANT	-3.085 (-3.035)	-2.043 (-2.125)
ASTHMA	0.8425 (2.328)	0.6724 (1.851)
BRONCH	3.774 (7.663)	2.936 (6.668)
SHRTWHZ	1.494 (3.683)	1.235 (3.428)
FLEMCO	1.458 (4:038)	0.2526 (0.8558)
HAYFEV	1.110 (3.509)	0.6613 (2.365)
BURB	-1.431 (-2.728)	-0.7330 (-1.539)
ACE	0.2986 (0.1596)	2.042 (1.177)
EXPWORK	---b	---b
ACCAR	-0.3485 (-0.8885)	-0.4395 (-1.364)
ACCEN	-1,9961 (-2.834)	-0.6291 (-1,829)
03	-0.1672 (-0.5638)	0.1252 (-.4475)
CO	1.279 (1.259)	-0.06285 (-0.06356)
NO2	0.5475 (0.7744)	0.6384 (0.9282)
σ_ν	2.617 (17.70)	2.454 (20.81)
σ_μ	1.827 (21.17)	
Chi-Square[c]	148.7	
P-Value for Wald Test	0.742	
Number of Iterations[d]	21	

[a]The dependent variables are the numbers of symptoms reported in the "chest and throat" category and in the "other" category. Asymptotic t-ratios are in parentheses. AGE is measured in centuries, CO in parts per hundred thousand, and 03 and NO2 in parts per ten million. All remaining explanatory variables are dummies. Note the long term health status dummies do not represent mutually exclusive categories.

[b]Omitted due to convergence problems.

[c]The chi-square test statistic is $-2\ln\lambda$, where λ is the likelihood ratio, for a test of the null hypothesis that the slope coefficients in both production functions are all zero.

[d]The convergence criterion is 0.5 for the gradient-weighted inverse Hessian.

TABLE 3.--BIVARIATE TOBIT SYMPTOM PRODUCTION FUNCTION ESTIMATES: NORMAL SUBSAMPLE[a]

	Chest and Throat Symptoms	Other Symptoms
CONSTANT	-5.789 (-2.157)	-5.479 (-2.790)
HAYFEV	2.316 (1:614)	1.461 (1.871)
BURB	-1.388 -1.180)	-0.6248 (-0.8470
ACE	4.143 (0.7873)	7.075 (2.091)
EXPWORK	0.8707 (1.157)	1.329 (2.297)
ACCAR	-1.949 (-2.905)	-0.6705 -1.057)
NOTGASCK	-0.4613 (-0.6312)	-0.8565 (-1.594)
03	0.2757 (0.5867)	0.3592 (0.9674)
CO	0.1788 (0.07729)	-0.07200 (-0.05241)
NO2	1.841 (1.162)	1.069 (1.127)
σ_ν	3.204 (10.15)	2.435 (11.31)
σ_μ	1.828 (10.44)	
Chi-Square[b]	69.81	
P-Value for Wald Test	0.610	
Number of Iterations[c]	20	

[a]The dependent variables are the numbers of symptoms reported in the “chest and throat” category and in the “other” category. Asymptotic t-ratios are in parentheses. AGE is measured in centuries, CO in parts per hundred thousand, and 03 and NO2 in parts per ten million. All remaining explanatory variables are dummies.

[b]The chi-square test statistic is $-2\ln\lambda$, where λ is the likelihood ratio, for a test of the null hypothesis that the slope coefficients in both production functions are all zero.

[c]The convergence criterion is 0.5 for the gradient-weighted inverse Hessian.

TABLE 4.--UNIVARIATE TOBIT SYMPTOM PRODUCTION FUNCTION ESTIMATES[a]

	Impaired Subsample	Normal Subsample
CONSTANT	-2.253 (-1.263)	-6.085 (-2.329)
ASTHMA	1.0333 (1.953)	
BRONCH	4.649 (7.708)	
SHRTWHZ	1.909 (3.242)	
FLEMCO	1.769 (3.607)	
HAYFEV	1.574 (3.137)	2.216 (2.378)
BURB	-1.830 (-2.927)	-13623 (-1.126)
ACE	1.200 (0.4034)	6.351 (1.165)
EXPWORK	---b	1.725 (2.039)
ACCAR	-0.5900 (-2.585)	-1.260 (-2.425)
O3	0.1629 (0.4846)	0.5941 (1.616)
CO	1.013 (0.8041)	0.3722 (0.2163)
NO2	0.8930 (1.130)	1.726 (1.784)
σ_ν	3.684 (37.29)	3.790 (22.47)
σ_μ	2.582 (15.84)	2.516 (8.822)
Chi-Square[c]	77.88	36.45
P-Value for Parameter Restrictions	0.623	0.562
Number of Iterations[d]	8	5

[a]The dependent variable is the total number of symptoms reported. Asymptotic t-ratios are in parentheses. ACE is measured in centuries, CO in parts per hundred thousand, and O3 and NO2 in parts per ten million. All remaining explanatory variables are dummies. Note the long term health status dummies do not represent mutually exclusive categories.

[b]Omitted due to convergence problems.

[c]The chi-square test statistic is $-2\ln\lambda$, where λ is the likelihood ratio, for a test of the null hypothesis that the slope coefficients in both production functions are all zero.

[d]The convergence criterion is 0.5 for the gradient-weighted inverse Hessian.

TABLE 5.--MARGINAL WILLINGNESS TO PAY TO RELIEVE SYMPTOMS AND AVOID AIR POLLUTION

	Impaired Subsample			
	Symptoms	O3	NO2	CO
Mean	$1.12	---[a]	---[a]	---[a]
Median	$1.09			
Maximum	$1.90			
Minimum	$0.81			
	Normal Subsample			
	Symptoms	O3	NO2	CO
Mean	$0.73	$0.31[b]	$0.91[b]	---[a]
Median	$0.70			
Maximum	$1.22			
Minimum	$0.49			

[a]Denotes coefficient not significantly different from zero at 10 percent level using one tail test in estimated equations presented in Table 4.

[b]Estimates of willingness to pay for reduced air pollution do not vary across sample members. In the computational ratio, respondent specific information appears both in the numerator and denominator and therefore cancels out.